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## Classifier Approaches for Liver Steatosis using Ultrasound Images

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### Abstract

This paper presents a semi-automatic classification approach to evaluate steatotic liver tissues using B-scan ultrasound images. Several features have been extracted and used in three different classifiers, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM) and k-Nearest Neighbors (kNN). The classifiers were trained using the 10-cross validation method. A feature selection method based on stepwise regression was also exploited resulting in better accuracy predictions. The results showed that the SVM have a slightly higher performance than the kNN and the ANN, appearing as the most relevant one to be applied to the discrimination of pathologic tissues in clinical practice.

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*Keywords:* Classifier, Liver Steatosis, Feature Extraction, Ultrasound

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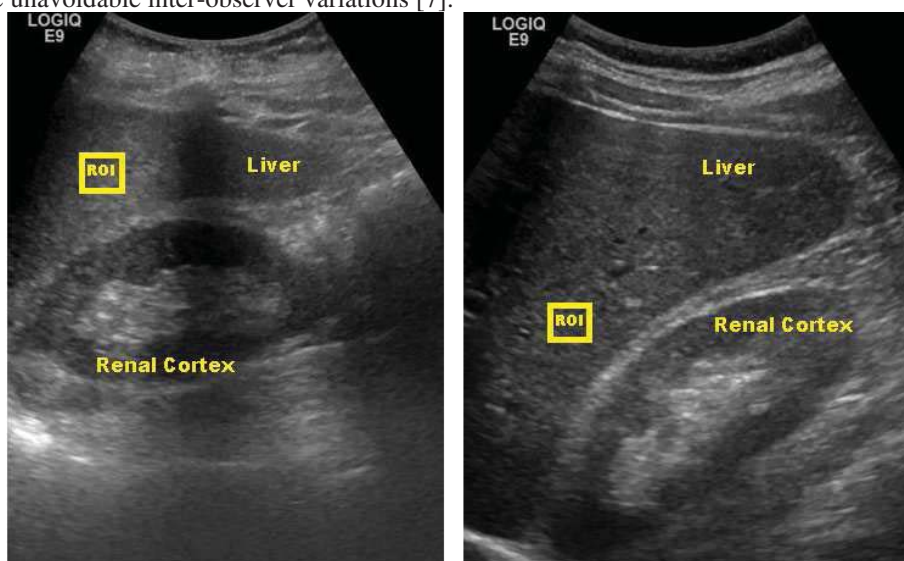
E-mail address: [jsilva@ci.uc.pt](mailto:jsilva@ci.uc.pt)

## 1. Introduction

LIVER steatosis (fatty liver) is related to the abnormal presence of triglycerides and other fats inside liver cells [1]. The fatty accumulation in the liver by itself is not a prejudicial situation if the fat content is under 10% of the total weight of the liver [1, 2]. This pathology can be associated with liver inflammation or can progress to it (e.g. hepatitis) and in an extreme situation can evolve to liver cirrhosis leading to permanent liver damage [2, 3]. However the disease can be reversible if detected in its initial stage [3, 4]. This pathology is commonly associated with some troubles such as obesity, diabetes mellitus, high blood triglycerides, and the excessive alcohol consumption [2].

The pathological changes introduced by this disease can be evaluated making use of ultrasound images (see Fig. 1), by characterizing the attenuation of the received echo signals; the liver echogenicity modifications in comparison to the renal cortex, and by the poor visualization of portal veins and diaphragm [5, 6].

The use of ultrasound images in fatty liver diagnosis is strongly dependent on physician's visual perception as the evaluation is done using the brightness levels [2]. In addition, the speckle noise present in the images makes the analysis troublesome. To overcome these problems, some authors recently proposed methods and tools based on computer-aided diagnosis (CAD) to help the physicians to clear up the B-scan images, then reducing the unavoidable inter-observer variations [7].



**Fig. 1.** Liver and kidney representation of steatotic (left) and normal condition (right)

To the present, several CAD systems have been applied for assisting physicians in the early detection and characterization of various pathologies using ultrasound images in organs as the liver, breast, thyroid and lungs [8, 9]. The CAD systems may be assisted by segmentation methods to identify not only the hepatic region but also the heart cavities [10-13], lungs [14-20] and also vascular or neural structures [21, 22].

For the liver case, the most commonly used features are related to textural measures by constructing spatial gray-level dependence matrices, also termed as co-occurrence matrices that were introduced by Haralick [23]. Other approaches as Fourier power spectrum [24] and Law's texture energy measures [25] have been applied within this context. In addition, the fractal concept developed by Mandelbrot [26] gives information about the roughness of natural surfaces. Nicolau et al. [27] was the first to introduce measures of echogenicity, eco-

texture, and liver-surface using ultrasound images. Also, Vehmas et al. [13], gave an important contribution for steatosis detection by measuring the liver and kidney echogenicity ratio. More recently a new method was proposed by Webb [28] that measures the fatty infiltration by using a computerized Heptorenal Index.

In the present work, a CAD system based on feature extraction and decision making is proposed to help the classification task of liver pathologies. Image features extraction was based on: first order statistics, co-occurrence matrix, run length matrix and fractal dimensions. Three different classifiers have been used for the features evaluation, namely the ANN, SVM and kNN. The classifiers performance was also studied in order to evaluate its applicability in the clinical practice.

## 2. Methods

### 2.1. Image acquisition and preprocessing

Ultrasound images were acquired at Coimbra University Hospital by using a GE Logic E9 ultrasonic machine with a 4 MHz convex probe. Each collected image has 8 bits of resolution and  $720 \times 960$  pixels. The data base consists of 177 echographic images obtained from 36 patients. A written approval for using the images in the research and development of diagnosis methods was requested to the patient. Two physicians classified the echographic images as normal and steatosis liver.

Regions of interest (ROI) with  $50 \times 50$  pixels have been extracted from each image. All regions in the image containing vessels and artifacts as well as the ones outside the organ boundaries have been discarded. The data set consisted of 131 ROIs for steatotic livers and 131 ROIs for normal livers. The feature extraction procedure and the classifiers implementation were carried out in MATLAB.

### 2.2. Computer-aided diagnosis system

The parameters extracted from images could help the decision making process when certain pathologies need to be evaluated. The decision process is related with statistics analysis, which has to do with grouping data with similar characteristics creating a specific class. The developed CAD system architecture is composed by three modules: feature extraction, feature selection and classifiers.

#### 2.2.1. Feature extraction

The proposed methodology extracts features based on different approaches characterizing the echogenicity of the B-mode images. Thus, several features have been derived from the first order statistics, gray level run length matrix, gray level co-occurrence matrix, law's texture energy and fractal dimension, comprising 325 features.

The first order statistics (FOS) deals with the information extracted from an isolated pixel that is not taking into account for the relationship between their neighbors. As a consequence, FOS is only able to describe the echogenicity of texture and the diffuse variation characteristics inside the ROI. However, as an advantage, these features are extracted quickly. Nine FOS features have been used: Mean, Variance, Standard deviation, Skewness, Kurtosis, Median, Entropy, Mode and Range [29, 30].

The gray level run length matrix (GLRLM) is a 2D matrix that is constructed for each ROI, describing the shape regularity and linearity of a pixel related to its neighbors. Each GLRLM  $p(i,j|\theta)$  element contains the total number of consecutive runs of length  $j$  at gray level  $i$  and direction  $\theta$ . The term "run" means the total number of consecutive pixels, which have the same gray level and are in the same direction. Different GLRLM have been estimated for the following  $\theta$  values:  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$ . A total of forty-four features were extracted [30, 31].

The gray level co-occurrence matrix (GLCM) gives relevant information about the inter-pixel relationship, periodicity and spatial gray level dependencies [31]. The analysis consisted in the construction of nine different GLCM considering angles between pixels of  $0^\circ$ ,  $45^\circ$  and  $90^\circ$ , for inter-pixel distance equal to 1, 2 and 3. Twenty-two descriptors have been extracted from each ROI [32], producing 198 features (22 GLCM features  $\times$  9 different GLCM).

The law's texture energy (TEM) consists in the application of 2D-masks to the image in order to enhance some properties. The masks are originated by the combination of five 1D kernels with each other. The convolution of each mask with each ROI allows extracting typical features as media, standard deviation, kurtosis, skewness and entropy. Thus, a total of 70 Laws' texture features (14 filtered texture image  $\times$  5 statistical features) have been computed from each ROI [31].

The fractal analysis is typically used in images presenting a high level of similarity. The fractal dimension is a textural feature that contains information about the geometry complexity and irregularity of an image. A higher fractal dimension corresponds to a more complicated or "rough" image. The box-counting was the selected for estimating the fractal dimension. The extracted features from this fractal are the mean, standard deviation and the lacunarity [33].

### 2.2.2. Feature selection

Generally, some of the used features are strongly related with each other. To reduce the complexity and some redundancy, a feature selection (FS) method has been applied with the specific purpose of improving the performance of the system. A stepwise regression has been used that is a statistical technique used for determining the features having significant relationships with the considered classes.

At each step a feature is included or removed from the considered model depending on its calculated p-value. To be added in model the p-value must have less than 0.05 and to be removed p-value must be less than 0.1. At the end, all selected features have a significant relationship with the clinical condition [34].

### 2.2.3. Classifiers

In order to prevent some features dominance each feature was normalized between -1 and +1 before using them in the classifiers [35]. As already mentioned, three different classifiers have been used providing a binary representation of the classes in terms of normal and steatosis.

The Artificial Neuronal Network (ANN) classifier is inspired in the biological nervous system model. Its simpler structures are neurons that can be interconnected in different configurations. The multilayer back-propagation algorithm was used due to its proven efficiency in neuronal network learning [36, 37]. The classifier training begins with random weights and bias for the input and hidden layers. The input vector consisted of 385 elements (nodes), one hidden layer with three neurons, which were obtained using the method of trial and error, and one output layer [38].

The Support Vector Machine (SVM) classifier aims to find the hyperplane in a high dimensional feature space that best separates the classes [39]. In the training process, the weights and bias vector are calculated by using a minimizing cost function [40]. Whether SVM is unable to find a separated hyperplane, then it is applied a kernel function to the original data for its transformation to a feature space of higher dimension. In this paper the linear kernel function was adopted since it provides better results comparing with the other ones[40].

The k-Nearest Neighbor (kNN) classifier uses a distance measure to make predictions about the class of the new test sample. The classifier assigns a test sample to the class of the majority of its k-neighbors. In the present work it was considered the Euclidian distance metric and the majority rule of the nearest neighbor when a tie occurs [41].

#### 2.2.4. CAD system performance

The performance of the proposed CAD system was evaluated using the overall accuracy that expresses the correct percentage of classifier predictions [42]. It has also been analyzed the Receiver Operation Characteristic (ROC) that represents the tradeoffs between hit rate (True Positive Rate) and false alarm rate (False Positive Rate). This tradeoff is especially important in medical imaging studies once it differentiates the misclassified data between normal and steatotic conditions in opposition with what occurs in the overall accuracy measurement [42]. The result extracted from the ROC is the area under the curve (AUC), which can vary from 0.5 (random discriminatory accuracy) to 1.0 (perfect discriminatory classifier) [43].

It was implemented a 10-fold cross-validation method, which randomly divides the dataset into ten groups where nine of them are used for training and one for classifiers testing. This procedure is repeated until all groups have been used in the testing. The final result corresponds to the average accuracy estimated for each iteration and to the AUC assessed by merging the test results for each classifier [43].

### 3. Results and Discussion

In this work, a total of 325 features have been extracted from each ROI of liver ultrasound images, namely 10 using FOS, 44 using GLRLM, 198 using GLCM, 70 using TEM and 3 using Fractals approach.

Three different classifiers have been considered for evaluation, as illustrated in table I and table II. According to table I accuracy values are very similar thus they do not provide a discriminative difference between all classifiers. Moreover, the AUC measure which is, by definition, related with sensibility and specificity of the classifier is slightly higher in SVM classify. Considering the AUC and accuracy value SVM is the classifiers that seem to better performed in the studied data, bearing in mind its proximity with ANN.

Table 1. Results for all Features.

	Classifier		
	ANN	SVM	kNN
Accuracy (%)	65.27	66.41	69.08
AUC	0.69	0.72	0.53

The stepwise regression method has been used for obtaining the most relevant features. It has led to an optimal subset of 7 features, including one from FOS, two one from GLCM and five from TEM approaches. An additional classification procedure was carried out starting with the classifiers training using the selected features subset and the 10-cross validation procedure. The accuracy and AUC results are shown in table II.

Table 2. Results using Feature Selection.

	Classifier		
	ANN	SVM	kNN
Accuracy (%)	76.92	79.77	74.05
AUC	0.83	0.88	0.48

Comparing the results shown in table I and table II, it can be said that the performances have considerably been improved by using the FS method. SVM followed by ANN appear to be the most influenced classifiers when using stepwise regression due the higher accuracy and AUC values. Despite the increase of accuracy in kNN classifier its AUC remains very low, assimilating with a random classifier.

Figure 2 shows the ROC plots according to the results in Tables I and II.

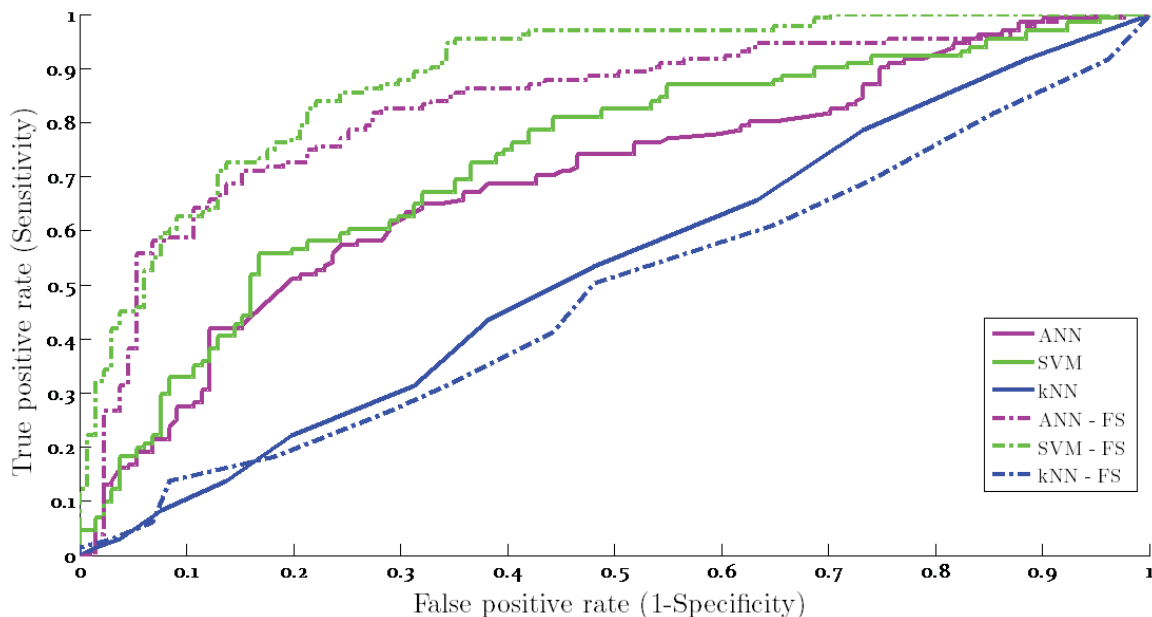


Fig. 2. ROC curves for the three classifiers with and without Feature Selection (FS) method.

As it was expected, the results suggest that the considered large number of features includes several “garbage features”, which usually damage the overall accuracy and increases the processing complexity [44].

Considering similar developed studies using classifiers [41, 45], it should be referred that the steatotic condition was not properly identified in [45] due the limited number of steatotic samples, and a feature selection approach was not used in [41], although the classifiers performed better.

Good classifier results were also reached in the works developed in [29], [46] and [47], however they were limited to a small feature set besides the usage of one single classifier, in opposite to the current work. Additional features showing promising results were also explored by the authors [3, 4], however, again, they were only limited to one single classifier.

#### 4. Conclusions

This work aimed to evaluate the performance of three classifiers for diagnosis of liver steatosis, using several extracted features from ultrasound images. The authors exploited clinical data assumed to be characteristic of normal and steatotic liver. The estimated features extracted from textural, histogram and fractal dimension approaches have led to encouraging results as inputs of the used classifiers.

Despite not having, on this level, a so clear distinction between the classifiers performance it was suggested that SVM would generally perform better due this good AUC and accuracy relation. When it was applied a stepwise regression which indicate the seven more discriminatory features, the classification system improved by 12.81 %, 14.38 % and 0.23 % for the ANN, SVM and kNN, respectively.



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